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The Geography of Mortgage Lending in Times of FinTech

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We analyze how banks' allocations of mortgage credit across regions change when an online platform enables them to offer to regions where they have no branches, staff or legacy. Unique data from an online platform with responses from different banks to each mortgage application yield three novel findings. First, banks offer more and cheaper credit to borrowers in markets less competitive offline. Second, banks offer more credit to more distant locations, where house prices appear less over-heated, and past price growth is less correlated with that in their existing portfolio. Third, over time offers become more automated, lowering operational costs.

Keywords: Mortgage Lending, Spatial Competition, Credit Risk, Diversification, Automation of Banking, FinTech, Online Pricing

JEL Classification: G2, L1, R2

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1 Introduction

Every mortgage is associated with a specific location in which its collateral is based in a way in which other assets on bank balance sheets are not. This location matters for the lender in at least three ways. First, different regional markets are often characterized by different intensity of competition so that the same bank can earn higher margins in one market than in another. Second, regions matter also for risk management. To start with, collateral prices in one region may be deemed more over-heated than those in another. More importantly, as long as house prices in different regions are at least not perfectly correlated in up- and downturns, lending to one region may improve the diversification of the mortgage portfolio of a bank previously concentrated in other regions, while yielding smaller or no diversification benefits to a bank already concentrated in that region to start with. Third, beyond revenue and risk management considerations, different locations may also imply different operational costs, as lending to different locations may give a bank different potential for automation.

These three sets of considerations suggest that banks may have reasons to prefer lending to one location over lending to another. In practice however many banks cannot freely choose even across the full territory for which they hold a banking license, as they can traditionally acquire and serve new customers only in those regions in which they already have a sufficiently dense network of branches, adequately trained staff, and are sufficiently known to potential customers. Establishing all of this implies significant initial cost. Relatedly, as researchers we cannot directly attribute the geographical distribution of a bank's lending to its preferences, as part of it may result simply from legacies.

Both for banks and for us as researchers however, things have started to change with the appearance of FinTechs that offer online mortgage platforms where potential borrowers from across the country can apply for a mortgage and potential lenders from across the country can serve them. In this paper we exploit data from the Swiss platform Comparis.ch. Beyond breaking down historical legacies of geography, these data have two other major advantages. First, we observe mortgage applications pre-intermediation and subsequent lender responses and can hence distinguish demand and supply in a way not possible with data on completed contracts or data at even higher levels of aggregation. Second, we observe for each application not just the response from one, but from several different banks. This allows us to analyze how different banks respond to the same borrower and thus break any endogenous matching of different types of borrowers to different types of lenders. Following pioneering work by Khwaja and Mian (2008), this feat has been achieved more recently by several papers on bank lending to large firms with more than one bank relationship, such as Jimenez et al (2012, 2014). By contrast, it is less common for households to entertain active relationships with several different banks, or at least for researchers to observe relationships with different banks for the same household. Identification of the quality of Khwaja and Mian (2008) has therefore, to our knowledge, been achieved for lending to households only by two papers so far. First, Basten (forthcoming) was the first to exploit the Comparis data analyzed here and found that higher counter-cyclical capital requirements caused more affected banks to raise prices relatively more, and thereby caused a shift of new lending from more to less affected banks. Second, Michelangeli and Sette (2016) obtained responses from different banks to the same household by sending randomized simulated mortgage applications to different banks.

Analyzing data on multiple banks' responses to each of 6'920 household mortgage applications made through the Swiss online platform Comparis.ch between 2010 and 2013, we obtain three main sets of findings. First, we find that more online competitors lead banks to make more and better offers, in particular when offering to cantons (states) where offline competition has been less intense. This is in line with banks seeking to "get a foot in the door" in particular in those regions where they can expect to gain the most profitable follow-on business. This reasoning is based on retail clients subject to switching costs, so they tend to bring more revenues to banks they have dealt with before. For clients, especially those in so far less competitive cantons, the online channel thus yields more and better offers.

Second, we find that banks seek the online channel in particular to lend more to cantons more distant from their home cantons, to cantons where house prices are deemed less over-heated relative to those in their home cantons, or where past house price changes have been less correlated with those at home. Although we do not yet observe a noteworthy number of defaults in either closer or more distant locations, the type of lending analyzed and explained in more detail below warrants the interpretation that the increase in regional diversification which the online channel thus allows does overall improve the risk management on banks' mortgage portfolios. This is because for the standardized mortgage lending analyzed collateral values across the country are assessed with the same hedonic models, so being local offers limited to no extra information.

Third, we find that cross-sectionally banks automate mortgage lending decisions more for less risky applications as well as when they themselves are larger or more specialized in mortgage lending. More interestingly, we also find that the longer banks have been lending online the more they manage to automate their decision-making, which has the potential to lower banks' operational costs without unduly sacrificing the quality of decision-making.

In addition, we are able to analyze how much offers extended to literally the same household differ across lenders. We find more dispersion the higher the associated credit risk, and the lower the expected profitability of the canton offered to.

With our three main sets of findings, we contribute to several strands of the literature. First we contribute to the literature on how distance and technology affect the degree of competition in banking (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Degryse et al, 2009; Eichholtz et al, 2019) with results on how the role of distance is modified as sufficiently standardized bank lending moves to the internet.

Second, we contribute to the literature on the effects of regional diversification on bank risk-taking. There is by now an extensive literature that exploited the US interstate bank deregulation as evidenced by Goetz et al (2013, 2016) and references therein. While Goetz et al (2013) find increases in regional diversification to have reduced average stock market valuations of US bank holding companies, Goetz et al (2016) find that it did nonetheless overall reduce bank riskiness as measured by the standard deviation (SD) of bank stock returns as well as the Z-score or other risk measures. They argue that the hedging of idiosyncratic local risks dominated potential reductions in banks' ability to monitor loans located at a larger distance. While their risk measures cover banks' entire balance sheets, including loans to firms and other assets, we focus more specifically on how banks can better diversify specifically their mortgage portfolios, where local knowledge is arguably relatively less important. Furthermore, online lending decisions can still be made by the same central decision-maker, removing the agency problems between bank headquarter and local credit officers that may be associated with larger distance. The online platform analyzed may thus reduce agency costs even beyond the level analyzed by Berger and DeYoung (2004) who saw reductions in distance-related agency costs within US bank holding companies through improvements in information processing and telecommunications. With a view to more recent work on new technology labeled "FinTech", our results are consistent with those by Fuster et al (2019) who find that US lenders using newer technology ("FinTech") do not necessarily target riskier borrowers.

Third, we bring together the recent literature on how the internet changes price setting (see Gorodnichenko and Talavera, 2017, Gorodnichenko et al, 2018, and Cavallo, 2017) with an extant literature on rules or automation vs. discretion. Gorodnichenko and Talavera point out that online sales are characterized by lower frictions of price adjustment, easier search and price comparisons, and a more limited influence of geographical barriers. They then show empirically that this leads to more frequent price adjustments and therefore to faster price convergence in response to nominal exchange rate movements, yet some persistence remains. In the lending setup we study, prices can be adjusted more easily also offline as each client receives an offer customized to his or her particular risk characteristics. But the lowering of search costs and removal of geographical barriers are likely to matter here as well. We investigate for which cases in particular this greater ease for customers in comparing prices customized to them reduces the degree of discretion.

The remainder of this paper is structured as follows. Section 2 introduces our hypotheses in the areas of respectively competition, risk management, and automation, as well as on the dispersion of offers received by each household. Section 3 then introduces our data and Section 4 provides more details on how we empirically analyze each area. Section 5 provides our results and Section 6 concludes.

2 Hypotheses

In this section we develop hypotheses, based on prior literature as well as economic intuition, on how the internet channel changes mortgage lending along the three dimensions of respectively competition, risk management through regional diversification, and automation. *In addition,* we develop a hypothesis on which types of borrowers we expect to attract the most diverse set of offers.

2.1 Hypotheses on Competition

With the appearance of the online channel, we need to consider both direct competitors who also offer mortgages online and indirect competitors who offer to the same market offline. For direct competitors intuition follows the lines of basic models of banking competition such as the oligopolistic version of the Monti-Klein model as outlined in Freixas and Rochet (2008). There banks set lower optimal lending margins to obtain sufficiently large lending volumes the higher the number of competitors. So we posit

Hypothesis 1a: *Banks offer prices with lower margins the higher the number of online competitors.*

In the basic oligopolistic version of the Monti-Klein model, banks optimize lending and deposit business separately, with any difference in volumes being lent to or borrowed from the interbank market. Furthermore, they do so for a single period only. More realistically, clients in retail banking tend to buy packages of services from the same bank including several components of mortgage loans, mortgage loan refinancing, deposit accounts, transaction accounts, or investment advice. One key reason why customers do not shop around afresh for every banking service they need are switching costs. Thus Beggs and Klemperer (1992) mention in their pioneering paper on switching costs as one of two examples the effort required to close a transactions account with one bank, open one with another, and transfer all transactions information. Referring more specifically to lending, Sharpe (1990) and the refinement by von Thadden (2004), as well as Chapter 3.6 of Freixas and Rochet (2008), point out that lending requires the bank to make some upfront investment into screening and monitoring the client, which has already been made when the loan needs to be renewed, and may be required even less when the bank has furthermore gained additional information about the client during past interactions. As a new lender would still need to pay these costs and typically pass them through to the borrower, the existing lender can add a markup for new lending. Sharpe (1990) then points out that such a setup "drives banks to lend to new firms at interest rates which initially generate expected losses", expecting that later markup increases make this worthwhile.[1]

For online offering of mortgages, the opportunity to earn more with a client won now implies that it is particularly attractive to gain new clients in cantons where competition has so far been less intense and on these grounds we posit:

Hypothesis 1b: *Banks offer prices with lower margins the* ***less*** *intense is offline competition in a canton.*

In addition to measuring the intensity of pre-existing competition in offline mortgage markets with the standard Herfindahl-Hirschmann Index (HHI), as explained in more detail in our strategy section below, we are also interested in the effect of banks meeting their competitors in other markets. Following Edwards (1955) idea of a "linked oligopoly", we thus posit:

Hypothesis 1c: *More multi-market contact increases banks' incentives to collude and hence leads them to behave less competitively.*

In their analyses of how market power influences loan pricing, Degryse and Ongena (2005) found that firms must on average pay higher prices the smaller the *distance* to the bank, relative to other banks. Similar findings were made for other markets by Petersen and Rajan (2000) as well as by Agarwal and Hauswald (2010). As switching banks would imply higher travel costs for periodically required in-person meetings, a bank that is located closer to a client than its competitors can thus exploit the extra convenience it can offer along that dimension by adding a larger margin. Of course such larger margins may then also reflect the additional costs to the bank of maintaining a larger network of branches that allow it to be the closest bank to a larger number of customers. Given these findings, we might *at first sight* expect offered lending margins to increase in distance also in our setup.

However, the financing of owner-occupied residential property in Switzerland differs from that of firms along at least two relevant dimensions. First, unless there is a severe crisis, residential mortgage borrowers typically do not need to see their bank after their mortgage initiation. This may be different in countries like the UK in which it is not uncommon for households to increase their mortgage loan when house prices have been rising in order to take out equity, or in countries like the US where households may choose to repay their mortgage early when interest rates have fallen. In Switzerland by contrast, taking out equity is uncommon and strategic early repayment is ruled out through high early repayment fees. Second, for mortgage lending the distance between bank and borrower matters not only in terms of market power, but at least as much for the bank's risk management. While, depending on its

[1] In line with this, Basten and Mariathasan (2018) find that Swiss banks decided to leave deposit rates non-negative even in times of negative interbank rates. This made the deposit business per se loss-making, yet banks prioritized retaining their deposit clients in the expectation of making profits from them again later.

sector, a firm whose sales area is struggling economically may often have some leeway to sell to other markets so that its ability to repay need not be tied to the economic developments in one particular region only, a house is by definition immobile and its value therefore intimately tied to the economic well-being in its area. Thus how a bank distributes its mortgage portfolio geographically matters for risk management. *How* it does is hence what we address in the next subsection.

2.2 Hypotheses on Regional Diversification

As mortgage lending to different regions implies different risks, we can interpret the margins implied by the prices offered as an indicator of how keen a bank is to lend to different regions, keeping fixed personal borrower characteristics and rate fixation period. On the one hand, risk managers may want to consider the fact that historically economic downturns in different regions are not fully synchronized due to inter-regional differences in economic specialization and in immigration patterns. Therefore probabilities of default and collateral values may also behave differently. So a bank can reduce risks to its mortgage portfolio by allocating a larger share to regions expected to exhibit a lower house price correlation with those in which it has so far conducted the majority of its mortgage lending. Indeed, Quigly and Van Order (1991) analyzed how actual mortgage *defaults* in the US are correlated intra- and inter-regionally and infer that mortgage portfolios are indeed riskier if they are less regionally diversified. As a consequence, they suggest that capital requirements associated with mortgage lending should be higher not only when the loan-to-value (LTV) ratio is higher but also when the portfolio is less diversified.

On the other hand, firstly a bank's risk managers may instead prefer to focus their lending on fewer regions so that it pays to collect more information there. This sensible argument is made by Loutskina and Strahan (2011) and empirically confirmed for the US market. Further, Favara and Giannetti (2017) show both theoretically and empirically that a bank with many mortgages in the same region can better internalize the negative externalities of collateral liquidations on the prices of other nearby collateral in an episode of increased defaults. This by itself would speak in favor of seeking to sufficiently dominate one area in order to internalize and therefore ideally remove that externality. Finally, Agarwal and Hauswald (2010) show that banks find it easier to screen firm lenders located closer to them, which is typically the place where a bank has already done most lending in the past. In the same vein, Eichholtz et al (2019) find US banks add margins increasing in distance when pricing mortgages underlying Commercial Mortgage Backed Securities (CMBS) and interpret their measure of distance as a proxy for reduced access to soft information.

To assess whether the benefits of hedging against idiosyncratic local risk or agency problems associated with greater distance dominate empirically, Goetz et al (2016) analyze the effects of US interstate branching deregulation and find that it does overall reduce bank risk, both when measured as the standard deviation of bank stock returns and when measured by Z-scores or other measures. This is so despite the fact that Goetz et al (2013) find greater regional diversification to reduce banks' average stock prices. In fact, already Berger and DeYoung (2006) show that technological progress, associated in their case with more credit scoring based on more hard rather than soft information as well as with more advanced telecommunication technologies, can reduce the agency costs associated with greater distance. This confirmed empirically arguments made theoretically by Stein (2000).

More specifically in the segment of lending studied here, regulation restricts the maximum LTV ratio to 90% and the maximum LTI ratio to effectively 6, so that none of the mortgages is as risky as some uncollateralized lending can be. More importantly, collateral values are typically not assessed physically, but through hedonic models bought from one of three consulting companies and are based on the *same* model for all of Switzerland. Finally, all banks have the same hard information on each customer and no soft information in the sense relevant e.g. in the setup of Eichholtz et al. Therefore the context complies with one characterized by Stein (2000) as based fully on hard rather than soft information. The only dimension along which a geographically closer bank might reach a different assessment on the basis of the same information is that it may attach a more or less positive value to the applicant's postcode area than a bank with less local knowledge. Therefore we expect the diversification motif to dominate and posit:

<u>*Hypothesis 2:*</u> *Banks will offer* ***better prices*** *to borrowers, after fully controlling for both lender and borrower characteristics, when:*

(a) *The borrower resides* ***a longer distance away*** *from the bank's headquarters.*

(b) *Real estate prices in the applicant's region are deemed* ***less over-heated*** *relative to prices in the bank's home region, especially for applicants with higher loan-to-value (LTV) ratios.*

(c) *House prices in the canton have historically exhibited a lower* ***correlation*** *with those in the canton where the bank is headquartered.*

All four dimensions are related to the distribution of the *bank's pre-existing mortgage portfolio* across Switzerland's 26 cantons: As all banks in our sample have on average larger fractions of their pre-existing mortgage portfolios in their home canton or directly neighboring cantons, lending to cantons that are further away in kilometers or driving minutes, whose prices are deemed less over-heated relative to those in the bank's home canton, or where house price growth is historically less positively correlated with that in the bank's home canton, can all improve the bank's risk management.

2.3 Hypotheses on Automation vs. Discretion

Any of the determinants of mortgage pricing discussed in the previous subsections can be effective by automating rules, through a computer or by communicating common policies for staff to follow. Alternatively, if staff retain sufficient leeway they may take into account also other factors. In the context studied, we dispose of all hard information the bank received through the Comparis platform and would therefore expect less heterogeneity in offers than in contexts in which loan officers may dispose of additional soft information. Yet the same information on an applicant's postcode may be interpreted differently by different loan officers or on different days.

An interesting way to formalize this idea is to build on the model of multiplicative heteroscedasticity formulated by Harvey (1976) and used in a bank lending context by amongst others Cerqueiro et al (2011). That paper finds more discretion for loans that are smaller, unsecured or go to smaller and more opaque firms, which can be rationalized by the idea that decisions in these cases are harder to automate well and are hence more likely to be escalated to (senior) staff. In our context, all loans are mortgages and hence all are collateralized, but we posit:

Hypothesis 3a: *We expect more discretion in loan pricing for applications that at first sight appear more risky, i.e. applications with higher loan-to-value (LTV), or higher loan-to-income (LTI) ratios, or less standard collateral.*

Beyond borrower characteristics, we hypothesize that the amount of discretion is likely to vary also with bank characteristics. In particular, banks that are larger or more specialized in mortgage-lending likely have more observations on which to calibrate automated lending decisions, and may also find it worthwhile to pay a higher fixed cost for fine-tuning such rules. Therefore we posit:

Hypothesis 3b: *We expect less discretion from banks that are larger or from banks more specialized in mortgage lending.*

Both considerations apply to online lending as much as to the offline lending analyzed e.g. by Cerqueiro et al, yet the online channel is to some extent different in that banks will learn only over time how attractive to borrowers they must shape their offers to have them accepted. On these grounds we posit

Hypothesis 3c: *We expect that discretion decreases, or put differently automation increases, the longer a bank has been offering mortgages online through the Comparis platform here analyzed.*

2.4 Hypotheses on the Dispersion of Offers within each Household

Above we have connected the characteristics of responses to those of banks, those of applying households, and those of their interaction. But given that we observe for each household up to 10, more often up to 7, and on average a bit over 4 responses, another issue of relevance is how different these responses are. In the existing literature, both Gurun et al (2016) and Bhutta et al (2019) have demonstrated that the same (type of) borrower may end up paying different prices to different lenders. Gurun et al relate price dispersion to lenders' advertising and borrowers' deemed sophistication, while Bhutta et al relate it to to borrower risk and interpret this as reflecting not only different credit risk premiums but also differences in borrower sophistication and negotiation ability.

In our context, all applicants use by definition the same channel to compare offers from different lenders. In that setup, if in the extreme all banks followed exactly the same rules, a household might as well just talk to any single bank rather than paying to obtain multiple responses. A priori this is more likely for applications that according to the usually considered measures such as LTV and LTI ratios are safe and are thus likely to be attractive to all banks, whereas higher risks might still be attractive for some banks, e.g. when they are based on cantons whose house prices are historically less highly correlated with those in the banks's home canton, but less attractive for others. On these grounds we posit:

<u>Hypothesis 4:</u> *We expect that spreads are more dispersed for households with higher LTV or LTI ratios than for households with lower LTV or LTI ratios.*

Having developed these hypotheses, let us now consider how to operationalize tests of them.

3 Data and Institutional Background

3.1 Data Sources

The key data used for our investigation stem from the Swiss website *Comparis.ch.* Between 2008 and 2013, they operated a platform on which households could apply for mortgages and were then provided responses from several different banks. For reasons of data quality, we focus on 2010-13. The resulting data are unique and offer at least four advantages for our analysis. First, we separately observe demand and supply. Second, banks in their operation and we analyzing them can pin down the effects of banks' differential access to clients from different regions based on amongst others pre-existing branch networks. Third, we can rule out that different banks tend to interact with different types of clients. And fourth, we observe 100% of the information each bank also has on each client. Bank decisions cannot be based on prior personal interaction, so our analyses cannot be biased by the use of soft information.

Observations on how different banks respond to the same client have to the best of our knowledge until recently been achieved only in research on lending to corporates, such as Jimenez et al (2012) and Jimenez et al (2014). By contrast, households engaged in mortgage borrowing have not been observed to interact with several different banks. Yet Jordà et al (2016) and other papers have shown forcefully the importance of the key role of mortgage markets in causing banking, financial and general economic crises, given that mortgages tend to be the largest financial liability of most households as well as the largest class of assets for many banks. To our knowledge the first paper to observe how different banks respond to the same mortgage borrower is Basten (forthcoming) who uses the same Comparis data as we do here to analyse how banks have responded to Basel III counter-cyclical capital requirements.

For the present purpose, the data include two outcomes of interest. First, an indicator of whether a specific bank makes an offer to a specific client. Second, given that it does, the rate offered. Offers can consist of between 1 and 3 tranches of different amounts, which may differ in the rate fixation period as well as in the offered interest rate. For each tranche, we subtract from the offered mortgage rate the swap rate for the same fixation period applicable on the day of the offer, as available through Bloomberg. This is to reflect the bank's refinancing costs absent any maturity transformation and is the measure of refinancing costs commonly used in the market under study, see also Basten (forthcoming) and Basten and Mariathasan (2017). Finally, we compute the weighted average across the up to three tranches, with weights given by the fractions of the total mortgage amount attributable to the respective tranche. Prices offered here are indeed a key dimension along which banks can influence how many mortgage contracts they conclude each period. Thus Basten (forthcoming) shows, using the same data, how banks more affected by higher capital requirements increase offered mortgage rates more and thereafter end up with lower growth rates in their mortgage volumes. As we know each bank's name, we complement the

Comparis data with data from banks' annual reports on their total assets, mortgages over total assets, deposits over total assets, and capitalization.

Furthermore we add data on actual house price growth by region from Fahrländer Partner Real Estate (FPRE). Together with Wüest & Partner and IAZI, FPRE is the leading Swiss real estate consulting company who, amongst other services, provides hedonic models that allow banks to gauge whether the market price a mortgage borrower wishes to pay is deemed appropriate. On the basis of the same hedonic quality adjustments they also compute house price indices for different quality segments from which we compute year-on-year house price growth rates. Furthermore, FPRE also estimates the extent to which current average house prices are "over-heated" in the sense of exceeding those prices deemed sustainable on the grounds of fundamental factors like incomes, rents and population growth (FPRE and BAK Basel, 2009). Banks who are clients of FPRE or at least read their publications will be aware of their estimates explicitly, those who are not may be using other measures which are likely at least positively correlated with the FPRE estimates of over-heating. For our analyses, we lag both measures by one year to ensure the current figure can be known to all banks when making their decisions.[2]

3.2 Descriptive Statistics

Overall we start with 6'914 applications, which attract a total of 25'125 responses. 20'583 of these are offers and 4'542 rejections. Table 1 shows the corresponding Summary Statistics. To provide a picture that corresponds as closely as possible to the data used for the subsequent regressions, the summary statistics use the same number of observations as the regressions. Thus *Panel (A)*, which focuses on the key characteristics of the mortgage applications, assigns more weight to applications that received more responses. The number of responses varies between 1 (in 1.53% of cases) and 10 (in 0.04% of cases). Most applications received between 3 and 6 responses, the average application about 4 responses. The mortgage amount applied for, and which by design could not be adjusted by the responding banks, varied between CHF 100'000 and CHF 2'000'000, with an average value of about CHF 600'000. The LTV ratio varied between 15% and 90%, with an average value of about 65%. Here the maximum is shaped by the fact that for any mortgage violating the self-regulatory requirement of at least 10% of "hard equity" from the household, the bank willing to provide it would have faced a regulatory risk weight of 100% instead of on average about 40%. The Loan-to-Income (LTI) ratio varied between 0.69 and 9.62, with a mean of 3.59. Household income varied between CHF 48'000 and 600'000, with an average of

2 We focus here on the measure for apartments. FPRE computes an analogous measure for single family homes (SFH), which yields very similar results in our regressions.

close to CHF 170'000, wealth including pension fund wealth reached an average close to CHF 500'000, and average age was 46 years.

Next, *Panel (B)* gives the key regional characteristics. Average actual house prices across the 106 statistical regions and during our sample period were considered to amount to between 94% and 200% of sustainable prices by FPRE, with a mean of 130% reflecting the wide-spread perception that house prices were due to correct downward somewhat at some point, as reflected also in opinions by, amongst others, *SNB (2013)* or *FINMA (2014).* This deemed over-heating is the result of price growth since the mid-1990s, which during our sample period reached on average 4.79% p.a. for apartments and 4.07% for single-family homes (SFH). In that context, we observe between 4 and 14 different banks offering mortgages online through the Comparis platform in a canton. Offline, we observe that the intensity of competition in cantonal mortgage markets is characterized by Herfindahl-Hirschmann Index (HHI) values ranging between 0.12 and 0.29, and Multi-Market Contact (MMC) measures ranging between 0.05 and 0.40.

Looking at bank characteristics in *Panel (C),* where banks are again weighted by the number of responses sent out, total assets (TA) range between CHF 434 million and CHF 37.8 billion, with an average of 16.9 billion. Between about 40% and 91% of these, and on average 70% of them are invested in mortgages, which reflects the general focus of Swiss retail banks on mortgage lending, see also *Basten and Mariathasan (2018)*. On the liability side, the most important position for most banks are deposits, with a range between about 17% and 66% and an average size of 48%. The capital ratio ranged between 4.72% and 11.33% and averaged 7.25% of total assets. When sending out their responses, banks had accumulated experience with answering mortgage applications online through Comparis.ch for between 0 and 69 months. The maximum is reached for responses submitted in the last months of our sample, September or October 2013, by banks participating since the platform start in early 2008. The *average* response in the sample is sent out by banks that at that point in time had a bit over 34 months or close to 3 years of experience of bidding for mortgages through Comparis.ch.

Panel (D) finally gives the key characteristics of banks' responses. To start with, it shows that the average response was sent to a household located between 0 and 422km or 0 and 4.42 hours from the bank. Given this geographical setup, the average household receives a bit over four different responses. On average this takes about 97 hours or about 4 days, although a bit over half of all responses arrive already within 48 hours. About 82% of all responses are offers. The rate fixation period ranges between 0.25 years for mortgages where the rate adjusts to the CHF Libor interbank rate every 3 months and 10 years. The average of 7.4 years reflects that 10 years is the most common fixation period, as discussed in more detail in Basten et al (2017). The average rate offered amounts to 2.16%, which implies an average spread above the swap rate for the same fixation period of 0.90% or 90 basis points (bps). Yet the spread varies between 40 and 152 bps, so banks' eagerness to win a deal varies significantly.

4.3 Representativeness

An important question when analyzing data from online lending is how representative these are of the offline market. To analyze this, we start with the key risk characteristics of the households. The best available benchmark for this is SNB (2014). Based on a bank survey that covers the 25 largest mortgage lenders and thereby 80% of the market, it reports that 7% of mortgages start with an LTV value above 80%, which corresponds very closely to the value of 8% in our sample. Furthermore, they report 18% of households starting with a Payment to Income (PTI) ratio above 33%, where the annual payment is computed as 5% of the loan for interest plus 1% for amortization plus 1% of the loan for house maintenance. When we multiply our LTI ratios with 0.07, we find that 17% of households start out with a PTI ratio in excess of 1/3. While we cannot formally compare the two percentages with a t-test for lack of data on standard deviations in the SNB data, the differences of 1 percentage point each suggest that from the household side the Comparis data are overall representative of the offline market, featuring neither a flight of particularly risky households from offline to online lending nor a particular eagerness by particularly safe households to obtain better conditions online.

Next and at least as important given the focus of this paper on geography, Table A1 presents the distribution of all 6'920 mortgage applications submitted between 2010 and 2013 across the 26 cantons, in Column (1) in terms of absolute numbers and in Column (2) in percent. In Column (3) it then compares that distribution with the percentage of new mortgage borrowers in the Swiss Household Panel (SHP) by the Swiss Federal Office of Statistics stemming from each of the 26 cantons. A new mortgage borrower is defined as a household who first transitions from renter to home owner in 2008-13[3] and therefore has mortgage debt in 2014. Finally, Column (4) presents the distribution of cantons of all existing mortgages on bank balance sheets as of 2013. Overall, we find that the distribution of applications is quite representative of the market as a whole and is not for example biased toward more urban areas or toward any of Switzerland's four language regions.

Likewise, Table A2 contrasts the geographical distribution of the headquarters of the 27 banks in our sample with that of the universe of Swiss retail banks used in *Basten and Mariathasan (2018)*. That paper starts out from the universe of all Swiss banks and then zooms in on the 50 retail banks by following the supervisor's definition of a retail bank as one that earns at least 55% of its income either as net interest income or as loan fees. Of course the distribution of banks is less smooth in our sample than that of households given only 27 banks in total. Yet we observe that the sample includes banks from across the country with greater numbers of banks stemming from the most populated cantons Zurich, St. Gallen and Berne as well as Aargau and Basel. But it includes also representatives from

[3] We start in 2008 to make the distribution sufficiently representative.

French-speaking Geneva, Valais and Vaud, as well as from Italian-speaking Ticino. Overall this makes us confident that the findings presented below are representative of bank behavior across all of Switzerland. Given the extreme heterogeneity of Switzerland in terms of language, religion, topography and urbanization, it may furthermore be argued that despite the limited size of the country, behavior is also representative of that in larger countries.

Finally, Table A3 looks beyond geography. Panel A compares the characteristics of households in our sample to those of households in the Swiss Household Panel (SHP) who recently acquired real estate. Panel B compares mortgage risk characteristics in our sample to those reported in the SNB Financial Stability Report 2014. Panel C finally compares the key characteristics of banks in our sample to those reported for all retail banks in Basten and Mariathasan (2018). In all three cases, we report all characteristics that are available both in our sample and reported in the respective benchmark. Column (1) always reports the mean value, and in brackets the standard error, in our sample, and Column (2) those in the benchmark—except for Panel B as SNB (2014) does not report standard errors. Panel A thus shows that households in our sample have virtually the same average age, but a higher household income. While the difference is not significant statistically, we deem it is significant economically. We do not see any obvious way in which this would distort the results of our bank-focused analyses, yet this difference is to be kept in mind. With regard to mortgage riskiness, we find no relevant difference with respect to payment-to-income (PTI) ratios and the resulting affordability of mortgages. By contrast, the fraction of mortgages with an LTV ratio in excess of 80% in our sample is economically lower at 7% than the 16% reported by the SNB. While the picture on this is incomplete as SNB (2014) does unfortunately report only this dummy rather than the continuous LTV measure and does not report corresponding standard errors, we may yet take the difference to suggest that our mortgage applications are if anything *less* risky. This makes sense, since it is known that in the more standardized online business banks will if anything be less willing to accept very high LTV ratios. As we explain later, this is indeed what we find in terms of bank risk-taking, and apparently households have to some extent anticipated this in that the fraction of applications with LTV ratios above 80% is smaller. Finally, Panel C shows that banks in our sample have a very similar risk-weighted capital ratio, but tend to be somewhat smaller and more deposit-financed. This likely reflects the fact that for larger banks it is more easily worthwhile starting their own online platform for mortgage lending or expanding their offline branch network, whereas the Comparis online platform is particularly attractive for smaller banks.

4 Empirical Strategy

We organize our analyses around the areas covered in our hypothesis section above: competition, risk management, and automation, as well as the dispersion of offers within each household. Each regression table focuses on a specific (set of) regressor(s) of primary interest, but for comparability we seek to alternate whenever possible the same set of controls. Thus in each table Columns 1 and 2 for the outcomes offer and pricing respectively control only for household characteristics, while Columns 3 and 4 add key bank characteristics. Columns 5 and 6 replace bank characteristics with bank fixed effects. Finally, Columns 7 and 8 replace household controls with household fixed effects, except for *Table 2* where the main regressors of interest do not vary within each household, so that no household fixed effects and hence no Columns 7 and 8 are added.

In addition to all regressors displayed and discussed, regressions include year*month fixed effects to fully control for any time trends. Furthermore, we cluster standard errors by application. This yields 6’920 clusters, the size of which ranges from 1 to 10, has a mean of 4.2 and a SD of 1.4. So cluster sizes differ somewhat but not excessively so. It does not make sense to cluster by bank given that the data set includes only 26 banks. As a robustness check, we have clustered by bank*year and found results to be robust to doing so. However, we cluster by application in our baseline, for otherwise the cluster size would range from 2 to 2’500 and its SD of 800 would amount to more than half of the mean of 1’400. Alternative specifications in which standard errors are robust but not clustered also produce very similar results. That said, the following subsections add a few relevant details on our approach to each of the three areas of analysis.

4.1 Strategy on Competition

We start with the online market only and measure the intensity of competition there with the number of other banks also offering to applicants from the same canton. After that we broaden the focus to the entire mortgage market, including its larger offline fraction. We measure the intensity of offline competition primarily with the well-known Herfindahl-Hirschmann Index (HHI). It would take value 1 if a single monopolist held the entire market, whereas it approaches zero when market shares are distributed more or less equally among an increasing number of competitors. In the case of Swiss cantonal mortgage markets, it ranges between 0.12 at the lower end and 0.49 at the upper end, and has an average value of 0.19. The deviation from zero is driven to a significant extent by typically significant market shares of the local cantonal banks that exist in 24 of the 26 cantons. For data reasons, the HHI measure we use focuses on mortgage market shares only and does not explicitly capture shares in the markets for transactions, deposits or advisory services. As these other banking services are often sold together with mortgages, market shares in the other businesses can be expected to be highly correlated with the mortgage market HHI.

For robustness, we alternatively use the Multi-Market Contact (MMC) index as in Degryse and Ongena (2007). It is based on *Hypothesis 1c*, following Edwards' (1955) idea of a "linked oligopoly" under which multi-market contact increases banks' incentives to collude and hence leads them to behave less competitively. On the other hand though, Park and Penacchi (2008) find that the presence of more multi-market banks can *promote* more competitive behavior. So we need to look at the data to find out. Either way, the MMC measure for each canton sums the number of bank pairs present after weighting each pair by the number of other cantons in which this pair does also encounter each other. More formally, we denote the 26 cantons by indicator j, and the 180 banks with any mortgages in 2009 by indicators k and *l*. Then we let $D_{ij}=1$ if bank i operates in canton j and 0 otherwise. So $a_{kl} = \sum_{j=1}^{26} D_{kj} D_{lj}$ tells us for each pair of banks *(k,l)* in how many of the 26 cantons they encounter each other, and f_j indicates how many pairs of banks we encounter in canton j. Based on this, we compute $MMC_j = \frac{2}{26 f_j (f_j - 1)} \sum_{k=1}^{180} \sum_{l=k+1}^{180} a_{kl} D_{kj} D_{lj}$. Overall the resulting MMC measure ranges between 4.6% and 40.5% and reaches an average of 7.5%.

As both HHI and MMC index could potentially be correlated with the extent to which mortgage lending and house price levels have been growing in recent years, both tables control in addition to all household and bank characteristics also for year-on-year apartment price growth as well as year-on-year single-family-home (SFH) price growth in the year preceding the bank response of interest.

4.2 Strategy on Regional Diversification

After *Table 2* has analyzed how the online channel affects the role of competition in mortgage lending, *Tables 3* explores the effects of the internet channel on bank risk management. We start with driving distance between the bank's headquarters and the postcode area of the applicant. In alternative specifications available on request we used instead driving time, which in mountainous territory differs in some cases, but is highly enough correlated with distance that it yields qualitatively the same regression results. Following that, we look at the extent to which year-on-year house price changes in the applicant's canton have historically been correlated with those in the bank's home canton. Finally, we consider the extent to which prices in the applicant's canton are deemed over-heated relative to the extent to which this is the case in the bank's home canton.

4.3 Strategy on Automation vs. Discretion

Following analyses on both competition and risk management, we explore to what extent the responses to the factors discussed above are automated, to what extent we observe prices to fluctuate around the values predicted by these factors, and whether this extent differs between different types of responses. To do so, we implement regression models with multiplicative heteroscedasticity as introduced by Harvey (1976). In a two-step procedure, he suggests to first estimate the relationship between regressors and outcomes of interest, in our context regressing offered spreads on competition intensity and regional characteristics as explained above. In a second step, we can then compute for each observation the residual variation u_i^2 not explained by our model and regress its log on our regressors of interest. In our case, we start with the full set of household and bank characteristics used also in the analyses discussed above, and add indicators for whether the applicant wishes to finance a single-family home (SFH) or a less standard type of real estate (villa, multi-family-home, or holiday home) rather than an apartment. Following that, we look first at the same three measures of competition as in *Table 2* and then at the same three measures of relative riskiness as in *Table 3*. Following that, we analyze in addition how the extent of discretion relates respectively to how fast the response was sent, and to the number of months for which the bank has already been offering mortgages online.[4]

4.4 Strategy to Analyze the Dispersion of Offers within each Household

As we observe responses from multiple banks to each application, another dimension of interest is to what extent responses are similar and to what extent they differ. Each application receives between 1 and 10 and on average a bit over 4 responses. When we rank the first 7 responses, given that receiving 8 or 9 is rare, in ascending order by spread, average spreads are respectively 79bps, 90bps, 95bps, 99bps, 103bps, 107bps, 108bps. Gurun et al (2016) measure dispersion as the difference between the 95th and 5th percentiles of "mortgage expensiveness", defined as the residual a borrower pays relative to the mean price paid by a borrower *with the same characteristics*. As we focus on offers sent to *literarally* the same household, we observe only 2-4 offers for many households so that inter-percentile differences would arguably be too much driven by outliers. Therefore we follow instead Bhutta et al (2019) and measure dispersion as the standard deviation of prices each household receives. For *Table 5*, we thus compute for each household the SD of spreads in basis points, as well as the SD in percent of the mean spread, and analyze which application characteristics this varies with.

[4] Following Harvey (1976), we practically implement the estimates by Maximum Likelihood Estimation rather than by two-step estimation, to improve estimator efficiency.

4.5 Strategy to Further Probe the Robustness of our Results

As discussed above, all our tables widely vary the set of controls. Except for our analyses on competition, they include also variations that control even for household fixed effects and bank fixed effects, something not possible in more traditional setups where only one mortgage lender is observed for each mortgage borrower. Further, all specifications control flexibly for time trends by way of year*month fixed effects. We also probe the robustness to different ways of computing standard errors.

All that said, results on pricing up to this point could potentially be affected by potential biases from the fact that pricing is observed only *conditional* on the bank making an offer at all. Basten (forthcoming) focused specifically on the effects of new capital requirements, observed no response of offer propensities to them and could therefore analyze responses of pricing to the requirements without having to account for possible selectiveness of responses. But here we are interested in a wide variety of independent variables and our results below show that offer propensities do respond to some of them.

A priori we expect that either banks express their eagerness to lend to any given applicant exclusively through rationing (rejecting) or pricing, in which case we can analyze the two dimensions separately as in Basten (forthcoming), or that they use both margins of response to express the same preferences. In the latter case, less attractive applications should typically be more likely to be rejected *and* receive higher prices conditional on not being rejected. Price add-ons observed should then typically be a bit muted relative to those we would have observed if banks had had exclusively the pricing tool at hands.

One may argue that offers which were not made influence neither the intensity of competition nor banks' risk management, so that offers never made do not bias the coefficients of interest anyway. Yet *for completeness* we are interested in understanding whether selectiveness of offers affects coefficients in our pricing regressions. Hence, following Heckman (1979), we estimate a *selection equation* in which we regress an indicator for observing an offer on our regressors of interest plus a variable that does plausibly affect offer propensities but not pricing (*exclusion restriction*). Following that, our *outcome equation* repeats our pricing estimations but controls for the estimated propensity of observing an offer.

For the variable that plausibly affects offer propensities but not pricing, we use an indicator for whether an application and the resulting response are sent out in the second rather than the first half of a calendar year. This is based on the idea that many banks may set annual targets for their overall volume of mortgage lending and deny more often when upon receiving an application they are already closer to or even beyond reaching their annual target. By contrast, offered prices are arguably chosen with reference to prevailing refinancing costs, credit risks, and competition, which need not differ significantly between the first and second half of the year. While we cannot formally test whether the month of the year does really not affect pricing, the approach can yet give us some confidence that offers never made would not have yielded very different effects on the pricing than the offers actually made and covered in our baseline analyses.

These analyses are always based on explicitly sent offers and rejections. However, not all 26 banks do send an explicit response to all applications. Instead, some banks have pre-specified with the platform operator what type of applications they wish to be forwarded and respond to. For example one bank may prefer mortgage amounts up to CHF 1 million, while another may prefer only larger ones, or one bank may prefer to finance only apartments, while another is happy to finance also single-family homes. As we do not know the exact agreements on this, one potential concern is that the set of applications a bank chooses to respond to is correlated with another regressor of interest so that our estimates could be biased by another source of selectiveness here. To investigate this, we fill in the dataset to include all possible household bank combinations. Then we repeat our Heckman analyses treating any non-response in the same way as an explicit rejection. As our results turn out to be robust to both sets of Heckman analyses, we now present our results on the simpler specifications that do not account for possible selectiveness, and discuss our Heckman analyses in more detail only after that.

5 Results

Table 2 presents our results on Competition, *Table 3* those on risk management through the geographical allocation of mortgage lending, and *Table 4* on the extent to which banks' choices are automated. In addition, *Table 5* analyses in addition which types of applications attract a more diverse set of responses. Following that, *Table 6 s*hows how results differ when we consider also offers never made amongst our actual set of responses, while *Table 7* considers even bank-household *responses* never sent. Finally, *Tables A1-3* explore how representative the dataset is of the offline market.

In *Table 2* and *Table 3*, uneven column numbers show the results for the binary outcome offer vs. rejection using logit regressions on all 25'125 responses. Equal column numbers then show those for the continuous outcome pricing using OLS regressions. Offered prices are observed only for the 20'583 responses that are offers, which is why *Table 6* and *Table 7* explore whether pricing results are robust to accounting for possible selectiveness of price observations.

In *Table 2* and *Table 3* we always show the regressors of specific interest in those tables at the top, followed first by key household characteristics and then by key bank characteristics. Columns 1 and 2 start controlling for household characteristics only, while Columns 3 and 4 add also bank characteristics. Columns 5 and 6 replace bank characteristics with bank fixed effects. Finally, Columns 7 and 8 replace household characteristics with household fixed effects, except for *Table 2* where the main regressor of interest does not vary within households, so no household fixed effects are possible.

For household characteristics we focus on indicators for LTV ratios above 67% and 80% and loan-to-income (LTI) ratios above 4.5 and 5.5 respectively. The specific threshold values reflect frequent practice in the market[5] and for LTV ratios reflect also those thresholds above which Swiss banks following the Basel Standardized Approach (all banks in our sample) face higher risk weights leading to higher capital requirements and therefore higher refinancing costs (see Basten, forthcoming). The threshold indicators turn out to have stronger effects on the outcomes of interest than continuous LTV or LTI variables. In robustness checks available on request continuous LTV and LTI ratios fail to have a statistically significant effect on our outcomes of interest after controlling for the indicators displayed here. Furthermore, in line with common practice at the banks studied, we focus on the two risk characteristics LTV and LTI. When we additionally control for a household's total income, rental

[5] In partcular, banks deem applicants more risky if their Payment-to-Income (PTI) ratio exceeds 1/3. For computing the PTI ratio during the period analyzed, banks used «stress-test» interest rates of either 4.5% or 5%. In addition they assumed house maintenance costs amounting to either 1% of the loan value, or 1% of the house value, implying 1.5% of the loan value at an LTV ratio of 2/3. Finally, amortization was assumed to be either 1% of the loan value, or 0% when regulation did not require it due to an initial LTV ratio <= 2/3, or before June 2012. Overall the 9 resulting combinations implied annual mortgage service payments ranging between 5.5% and 7.65% of the loan. The requirement for this to not exceed 1/3 was then equivalent to LTI thresholds of between 4.36 and 6.06. Here we round these to 4.5 and 5.5, as these are LTI values used in regulation in other countries, such as the UK. Other, similar LTI values yield the same regression results.

income or non-labor income, for the household's wealth (including pension fund wealth), debt, age or the type of dwelling sought, which are also observed in addition to LTV and LTI, none of them changes significantly the coefficients on the regressors displayed here.

As one would expect, we find throughout that higher LTV or LTI ratios induce banks to offer less often and, conditional on still offering, to add a risk premium and therefore charge higher prices. This is in line with, amongst others, Campbell and Cocco (2015), who point out how higher LTV ratios tend to be associated with higher credit risk in mortgage lending. Furthermore, the about 50% of applications asking for banks to refinance their mortgage, rather than to finance their initial purchase, tend to receive better prices conditional on receiving an offer, even after controlling for the meanwhile typically lower LTV ratio and possibly higher incomes. This can be explained by the fact that household seeking a refinancing has already had his real estate screened and approved at least once by another bank and furthermore will have been servicing the mortgage already for a while. *Table 3* also finds that banks make an offer less often, and conditional on making require an extra risk premium for households from areas that have had higher house price growth in the preceding year, increasing downward potential.

When we focus instead on bank characteristics, we see that banks which are either larger in terms of total assets or have a larger fraction of their assets dedicated to mortgage lending offer more often and at more competitive prices. One plausible explanation of this finding, beyond risk management, is a higher operational efficiency. By contrast, banks that raise a larger fraction of their funding through deposits offer less often. Here one possible reason is that having more depositors provides a bank already with a larger pool of potential mortgage clients, so that it depends less on selling mortgages also through the online channel. Another is that in contrast to the second most important source of funding for Swiss commercial banks, covered bonds, deposits are typically thought to have shorter effective rate fixation periods. Thus financing mortgages – the majority of which carries fixed rates – with deposits tends to yield a profitable margin in the short run, but implies also more interest rate risk to be borne, or hedged at a cost. Finally, banks that are better capitalized tend to charge higher prices, possibly reflecting the fact that a larger fraction of funding raised through equity is typically thought to imply (more bank safety in crisis times but also) higher marginal costs for each unit of lending. After this general discussion on the effects of our main control variables, demonstrating the validity of our setup, let us now turn to our key regressors of interest.

5.1 Results on Competition

Table 2 looks at banks' responses to the intensity of mortgage supply competition in the canton of the applying household. Line 1 focuses on the most obviously relevant measure of competition, the total number of banks also bidding for mortgages in the applicant's canton through the Comparis platform. We find that with each additional online competitor the offer propensity increases by one percentage point and prices are 1bp lower, so that an increase from the lowest number of competitors, 4, to the largest number, 11, increases each responding bank's offer propensity by about 11 percentage points and lowers prices by about 11bps. This may not sound large for raw interest rates, but is arguably economically significant when considering that it is the difference in rates *after* fully adjusting for the rate fixation period (maturity), credit risk and other household characteristics, and key bank characteristics such as size or capitalization. Overall, we see this as confirming our *Hypothesis 1a,* whereby more online competition provides borrowers with more and better offers.

In the row below, we see that even after controlling for online competition, banks offer between 11 and 20% more often to a market that is hitherto characterized by a monopoly (HHI=1) than to a market hitherto characterized by maximally intensive competition (HHI=0), and conditional on making such an offer lower prices by between 36 and 46bps. This implies that 1 SD in HHI of 0.05 units raises the offer propensity by up to 1% and lowers prices by up to 2.3bps. This confirms our *Hypothesis 1b*, whereby banks will seize the online channel to enter in particular those regional markets where offline competition has so far been less pronounced and which they may hence expect to be more profitable also for possible follow-up business. Consistent with this idea is the finding that banks tend to slightly increase prices the longer they have been offering online mortgages to a canton, as evidenced by the positive coefficients on a bank's online experience.

Finally, the same *Table 2* adds in the third line also the MMC measure and finds that banks offer lower prices the more they face in that canton banks whom they encounter also elsewhere. Put differently, they respond to more multi-market contact in qualitatively the same way as to higher market concentration measured by the HHI, which is in line with the original "linked oligopoly" hypothesis by Edwards (1955) rather than with the findings of Park and Penacchi (2008) or those of Degryse and Ongena (2007) who find higher MMC values to affect banking in the direction opposite that of higher HHI values.

5.2 Results on Regional Diversification

As discussed in our hypothesis section above, the internet allows banks to more freely choose which regions to lend to on the basis of different intensities of competition, but also in view of differences in credit risk. Typically the further away from the bank a household is located, the less has the bank already lent in his area, which makes the area on the one hand a potentially useful addition to its portfolio, but on the other hand implies that the bank might lack relevant local information. On these grounds, our *Table 3* starts off by exploring how banks respond specifically to distance. While results on offer propensities are less clear than in a version that does not include price correlation and relative over-heating at the same time, Columns 4, 6 and 8 show that as soon as we keep bank characteristics fixed either through controls or through bank fixed effects, banks lower the offer price by between 1 and 3bps for each 100km of distance. Results are qualitatively the same when we replace driving distance in 100km with driving time in hours, available on request. Overall this confirms our *Hypothesis 2a*.[6] [7]

While distance is merely a proxy for the marginal contribution of an extra mortgage to credit risk in the bank's portfolio, relative price over-heating measures credit risk more directly. In a period in which collateral values appear somewhat over-heated in most to all regions following a prolonged period of historically low interest rates, a bank may not be able to entirely avoid lending to a region deemed over-heated, if it does not wish to entirely close down its mortgage business. But it may at least want to consider how over-heated collateral values in the applicant's region are deemed to be *relative* to those in its home region to which it has easier client access also without the internet channel analyzed here. We find that where prices are over-heated by 1 SD or about 17% more than in the bank's home canton, banks make up to 4.25% fewer offers. In line with this, offered prices are up to 4.93 (17%*29bps) higher. These findings confirm *Hypothesis 2b.* They show that, even after controlling for distance, banks do consider over-heating risks, as measured either by the FPRE measure we used here or another one sufficiently correlated with it, when choosing how they would like to geographically allocate their mortgage portfolio given the opportunity to choose without reference to their pre-existing branches.

However, what if predictions of relative price over-heating in different cantons turn out to prove wrong and those cantons where prices were thought less over-heated experience the largest price decreases and highest default rates? One way to tackle this risk is for a bank to diversify its portfolio across regions where prices are likely to develop differently, thus reducing their overall losses regardless of which region experiences larger and which one smaller price reductions. To analyze to what extent banks seek to do so, line 3 adds as a regressor the correlation between year-on-year house price growth in the applicant's region and that in the bank's home region (where banks typically have the largest share of their pre-existing mortgage portfolios). Past correlations are based on year-on-year growth rates in a house price index for medium-quality apartment prices since 1985 from FPRE consultants, but growth

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[6] Computed with the same GIS program, distance and time do despite sometimes mountainous geography exhibit a correlation of 0.99. Therefore a Variance Inflation Factor (VIF) tells us that we may regress offer indicators and offered spreads on either, but not on both at the same time.

[7] In line with these findings, additional regressions confirm also more explicitly that banks offer specifically lower prices the more their pre-existing mortgage portfolio is «under-represented» in a canton, i.e. the more that canton's share in the bank's mortgage portfolio falls short of that of the entire Swiss banking system.

rates on low or high quality apartments or single-family homes yield very similar regression results. These correlations are all positive: Within a country as small as Switzerland that is subject to the same monetary policy it is hard to find a region whose house prices can be expected to increase when those elsewhere decrease. Yet despite a common monetary policy the summary statistics show that as different cantons specialize in different economic sectors and tend to receive their majority of net immigrants from different countries, some inter-cantonal correlations are as low as 0.15, which does provide a good degree of diversification. This said, Line 3 shows that when responding to a canton whose house price growth exhibits a one standard deviation or 0.19 units lower correlation with the bank's home canton, banks' offer propensity is between 0.95% (Column 3) and 2.09% (Column 1) higher, and conditional on making an offer prices are up to 1.71bps (Column 2) lower. Overall we take this to confirm *Hypothesis 2c* and see some potential here for banks to indeed improve the diversification of their mortgage portfolios as the online channel allows them to regions not easily reached offline.

Overall, our findings on the effects of distance, relative house price over-heating, and inter-cantonal house price growth correlations – as well as additional findings on the role of whether a canton's share in a bank's existing mortgage portfolio falls short of that in the portfolio of the entire Swiss banking system — suggest that in a market where soft information is not present or important, banks can and do use the internet channel foremost to improve the diversification of their lending portfolio.

5.3 Results on Automation vs. Discretion

After exploiting extensively how banks' offering and pricing vary with competition and risk management considerations, the question arises to what extent outcome variation remains unexplained by these factors and whether that extent does again vary systematically, i.e. whether we have multiplicative heteroscedasticity of standard errors as formalized in Harvey (1976).

In that vein, *Table 4* shows in Columns 1, 3, 5 and 7 the results of the *mean equation* regressing offered spreads on different sets of regressors. Columns 2, 4, 6 and 8 then show the results of estimating the corresponding *variance equation*. It takes the log of the outcome variance unexplained in the mean equation and regresses it on independent variables of interest. To start with, we see here that Column 7 with its 20'583 observations and 12 regressors reaches an R2 of about 22%, and Columns 1, 3 and 5 which control for year*month fixed effects reach one of even 27-28%. This is significantly higher than for example in Petersen and Rajan (2002), where the R2 from analyzing what determines interest rates on business loans reaches merely 17-18%. The likely reason is that they analyze lending to small businesses, in which loan officers take into account a good deal of soft information, whereas in the setup analyzed here banks have only the hard information we have as well.

Nonetheless, our R2 is by no means close to 100%. In fact, our Columns 2, 4, 6 and 8 show that the amount of rate variation which our model cannot explain does vary systematically with a number of regressors of interest. Starting with household characteristics, we find throughout all 7 columns that when the applicant's LTV ratio exceeds two-thirds, then the squared residual increases by 38-46% and hence the standard deviation of prices offered increases by 6.2-6.8%. While low-LTV applications may be dealt with by more junior staff following set rules, or may even be delegated to a computer, the higher the LTV ratio and hence the higher the estimated credit risk the more often does the decision have to be escalated to more senior staff, under whom our set of standard regressors need not always have the same marginal effects. Relatedly, we observe that the squared residual increases by 16-26%, and hence the residual by 4-5% whenever the proposed lending collateral is a less standardized object such as a villa, holiday home or multi-family house rather than more standard and hence easier-to-value apartments or single-family homes. This is consistent with the predictions in Petersen and Rajan (1995) whereby banks exert more discretion when lending to more "opaque" and hence harder-to-value firms. The findings support *Hypothesis 3a.*

Looking at bank characteristics, we find that each percent increase in the responding bank's total assets reduces the squared residual by between 8-20% and hence the residual by 2.8-4.5%, while each percentage point increase in a bank's share of total assets allocated to mortgages reduces the squared residual by 2-3% and hence the residual by 1.4-1.7%. Both findings confirm our *Hypothesis 3b*, whereby larger or more mortgage-specialized banks have more previous observations to allow them devising more reliable rules, and have stronger incentives to invest fine-tuning such rules.

Having thus analyzed the role of standard household and bank characteristics, we look next at the same measures of competition intensity and credit risk as analyzed above. Column 2 shows that more web competitors ceteris paribus lead banks not only to offer lower prices but also to automate their business more: Thus each extra web competitor is associated with a reduction of 6% in the squared residual and hence a reduction of 2.5% in the residual. Differences in HHI and MMC by contrast have no statistically significant effect on the amount of discretion after controlling for the number of web competitors. The finding for the number of web competitors however is consistent with predictions following from the work by Petersen and Rajan (1995).

Next, Column 4 shows that for each extra 100km of distance, squared residuals decrease by 12 and standard deviations therefore by 3.5%, as presumably loan officers have less additional information about specific postcode areas that they feel useful to take into account and hence decide more rule-based than "closer to home". This is consistent with the theoretical predictions by Hauswald and Marquez (2006) in which banks seek to soften price competition closer to home by acquiring more private information so that they can threaten competitors from outside to end up with adversely selected customers. By contrast, in more distant places it does not pay to acquire the same amount of information to better select customers so that banks can only compete through lower prices (and might end up making less efficient lending decisions). In our context we can rule out the acquisition of private information at the level of individual households, as all banks have the same set of borrower-specific hard information and so do we. Some discretion may yet remain if a local bank draws different implications from observing the same postcode as a more distant bank. Column 4 also finds that for each percentage point for which regional house prices appear more over-heated, squared residuals increase by about 202% so that residuals increase by about 14%, the largest determinant of all so far. This is consistent with more discretion for higher-LTV applications, possibly implemented through internal rules that require decisions about riskier applications to be escalated to more senior staff.

Then, Column 6 finds that whenever a response is sent out in less than the median response time of 48 hours, squared residuals decrease by 18% and residuals therefore by 4.2%. This is likely precisely why they can be sent out faster. Finally, Column 8 shows that with each additional month for which the bank has been offering mortgages online through the Comparis platform, squared residuals decrease by about 2% and residuals therefore by 1.4%. Assuming as a simplified approximation that this marginal effect of each month of online experience is the same for all 69 months observed, this implies a decrease in discretion by more than 90% between the first and the last month of our sample. This can be seen to support *Hypothesis 3c*.

5.4 Results on Disperson of Offers

In *Table 5*, Columns 1 and 3 use as outcome the standard deviation of spreads within the set of responses received by each household, while Columns 2 and 4 use the same standard deviation but for robustness rescale it by the mean spread offerd to that household. Columns 1 and 2 control additionally for year*month fixed effects, while Columns 3 and 4 do not. As each household's set of responses consists by definition of responses from multiple different banks, we cannot analyse how the dispersion of offers is related to e.g. distance or the correlation of prices in the hosehold's and in the bank's canton, but we can analyse firstly how it varies with the three measures of competition intensity in the applicant's canton, and secoddly with applicant-specific risk factors.

Starting with the coefficient on the Herfindahl-Hirschmann Index (HHI), we find first that the standard deviation is on average about 26bps, or about 20% of the mean spread, lower in a (hypothetically) fully monopolized cantonal market. In a similar vein, we also find less dispersion the more other banks are also bidding online, although the size of this effect is below 1bp per additional competitor and therefore seems economically negligeable. By contrast, the effect of a more concentrated offline market does not, and suggests that most banks agree which cantons are most attractive to enter through the online channel.

By contrast, banks appear to agree less when the credit risk associated with a household is higher. In particular, we find that whenever the LTV ratio exceeds two-thirds, the SD of spreads is on average 4bps, or about 3% of the mean spread offered to that household, higher. In line with that, it tends to be lower for refinancing applications, which tend not only to have already reduced their LTV ratios but have also proven already for a number of years that they are able and willing to keep servicing their mortgage as agreeds with their previous financing partner(s). We take this to confirm our *Hypothesis 4*.

It can be attributed firstly to inter-bank differences in the ability and willingness to take on riskier clients, and secondly to the fact that borrowers with higher LTV ratios may still be more attractive for banks from further away so that house prices in their existing portfolio exhibit on average a lower correlation with those in the applicant's canton, than for banks already concentrated in that canton.

5.5 Robustness

In *Table 6* we explore how robust our effects on pricing are to controlling for possible selectiveness of where we observe an offer and hence a price in the first place. All columns control for bank fixed effects. Columns 3-8 control also for household fixed effects, while Columns 1 and 2 use instead household controls as the competition measures of interest there are invariant within each canton and therefore also within each household. More specifically, Columns 1-2 include the same three competition measures as in *Table 2* and Columns 3-4 include the three risk measures as in *Table 3*. Columns 5-6 and 7-8 include respectively the fast response and bank web experience measures as in *Table 4*. Within these four pairs, the first column shows always the results of estimating the *selection equation*, which atop all other regressors includes the 2nd semester indicator. The second shows the resulting main equation estimates.

To start with, results on the *selection equation* show that responses sent out in the second half of the year are between 8% (Column 1) and 11% (Column 11) less likely to be offers, so the instrument is certainly sufficiently strong. The *exclusion restriction* whereby pricing depends on the bank's own refinancing costs, risks and competition intensity but not on the time of year can by definition not be tested formally, but month-dependent pricing after controlling for all other regressors seems unlikely. As discussed above, offer propensities vary significantly also with amongst others household characteristics, competition intensity, and risk characteristics, suggesting that the pricing on offers never sent could differ from that on offers that are sent out.

The *Inverse Mills Ratio*, i.e. the product between the standard error of the residuals σ and the correlation ρ between the error terms of selection equation and outcome equation, is statistically significant at the 1% significance level and has a size of 0.15 to 0.16. This suggests that the error terms of the two equations are indeed correlated significantly. All estimates displayed here control for bank fixed effects and year*month fixed effects. Columns 3-8 control additionally for household fixed effects, while 1-2 have to make do with the standard set of household controls, as household fixed effects would be perfectly collinear with the competition measures of interest, which do not vary within each household.

Comparing the coefficients on our three measures of competition intensity with those in *Table 2*, we find the same coefficient discount per number of web competitors, a discount of 51 rather than 36-46 bps when increasing the HHI from 0 to 1, and a discount of 35 rather than 41-64bps when increasing the MMC from 0 to 1. So while sizes differ, sign and statistical significance are qualitatively unchanged. We also find a discount of 5bps rather than -1 to +3bps per 100km distance, a surcharge of 52bps rather than 2-29bps when prices are twice as over-heated as in the bank's home canton, whereas the MMC measure retains no statistically significant coefficient. Fast responses now cost 2bps more rather than 1bp less than slow responses and with each month of bank web experience they increase by 1bp rather than decreasing by 2bps (*Table 4*). These two differences sem economically negligeable.

Following these Heckman regressions on our baseline sample, *Table 7* investigates also whether our estimates might be biased by bank-household combinations where banks send no response rather than an explicit rejection. We fill in all possible household-bank combinations and treat non-responses like rejections. This inflates the dataset from 25'125 responses or on average about 4 responses per application to up to 180'839 possible household bank combinations or up to 26 per bank. Associations with the "fast response" indicator cannot be analyzed here, as we cannot sensibly define whether a non-response was "fast" or "slow". Looking at the results on competition intensity in Column 2, the discount associated with an extra web competitor remains again unchanged, that associated with more offline market concentration increases even slightly further to 58bps, while that associated with more mult-market contact decreases slightly to 32 bps.

The discount per 100km of extra distance increases from 5 to 8bps, the surcharge for more correlation returns to the statistically significant 9bps as in Column 2 of *Table 3*, while now more relative price over-heating appears to induce a discount rather than a surcharge. The coeffient on web experience is unchanged from the smaller sample.

Overall, we do note that some coefficients do change size when we account for either rejections or non-responses, but overall results are largely confirmed. Thus we deem it appropriate to focus at the baseline on the pricing of offers actually sent out rather than the hypothetical pricing of offers never sent out.

6 Conclusion

In this paper we have investigated how mortgage lending changes through the provision of an online platform where potential borrowers from across the country can apply and potential lenders from across the country can respond. For banks this removes the usual constraint that most banks can interact with most borrowers only if they maintain a branch nearby that borrower's location. For us as researchers the platform, which has provided us with all borrower information as forwarded to the participating banks, allows to attribute a bank's propensity to offer and the attractiveness of its offers directly to properties of the applicant's region, and its relationship with the bank's own location and prior portfolio. In particular, the fact that we observe the responses from different, and differently located, banks, as well as responses from each bank to different, and differently located, households, allows us to saturate most regressions with both household fixed effects (or characteristics) and bank fixed effects (or characteristics) and so to isolate the role of the location of each side and of their interaction. We thus obtain findings along three dimensions.

First, we observe that the more other competitors are also offering online to a region the more often do banks respond with an offer and the more attractive is the price they offer. At the same time, we observe banks to bid more attractive prices in particular for applicants from regions with hitherto more concentrated offline markets, suggesting that they seize the online channel to get "a foot in the door" in those markets. For potential borrowers, in particular those located in hitherto less competitive regions, this implies that the availability of an online platform can lead to more and better mortgage offers.

Second, in line with banks' general strife to use the online channel to enter profitable markets, we see that the average bank makes particularly attractive offers when bidding for clients in regions further away from its "home turf". In particular, they make more attractive offers also to regions where collateral prices are deemed less over-heated relative to those in the bank's home region, or where in the past price changes have been less correlated with those in the bank's home region. In that sense, the online channel allows banks to improve the inter-regional allocation of their mortgage portfolio and hence ceteris paribus improve their risk management in line with arguments in amongst others Quigly and Van Order (1991). We deem the risk management benefits from more inter-regional diversification to dominate potential increases in the cost of raising information on more regions, as validly raised by Loutskina and Strahan (2014), in the market analyzed. For collateral values here are assessed with the same hedonic models country-wide and information on borrowers are equally reliable regardless of the region. Yet we acknowledge that we cannot explicitly compare default rates on more versus less distant residential mortgage lending, as the period analyzed is characterized by a negligible incidence of defaults.

Third, we investigate explicitly dispersion of offered prices around those predicted by the set of factors discussed above, and interpret it as cases in which decision-making is not fully automated or is even escalated to more senior staff. As expected, we find more automation for safer loans, by larger banks, and by banks more specialized in mortgage lending. More interestingly, we also find that the degree of automation thus measured increases the longer the bank has been offering mortgages to individual customers through the online platform, suggesting that longer participation can help banks to reduce their operational costs. Importantly, absent a crisis we do not yet know for sure whether such automation increases the potential for erroneous decisions in the sense of under- (or over-) pricing underlying credit risk. We do however observe banks to price in all commonly considered mortgage risk factors such as LTV and LTI ratios, as well as estimates of regional house price over-heating, so we have no reason to suspect that banks are less careful when offering mortgages online than when they do so offline.

Overall our findings suggest potential improvements for borrowers as well as for financial stability that can be achieved through online platforms, so it will be interesting to see how the use of platforms with associated costs and risks develops going forward.

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Tables

Table 1: Descriptive Statistics

	N	Mean	SD	Min	Max
(A) Applicant Characteristics					
Year	25'125	2011	1	2010	2013
Month	25'125	6	3	1	12
Mortgage Amount	25'125	566'274	332'695	100'000	2'000'000
Refinancing (0/1)	25'125	0.46	0.50	0	1
Loan-to-Value (LTV)	25'125	64.50	17.30	15.00	90.00
I (LTV > 67%)	25'125	0.53	0.50	0	1
I (LTV > 80%)	25'125	0.08	0.26	0	1
Loan-to-Income (LTI)	25'125	3.59	1.52	0.69	9.62
I (LTI > 4.5)	25'125	0.23	0.42	0	1
I (LTI > 5.5)	25'125	0.08	0.27	0	1
HH Income	25'125	167'603	88'961	48'000	600'000
Rental Income	25'125	4'232	16'880	0	116'000
Other Income	25'125	9'381	28'329	0	200'000
Wealth incl. Pension Fund	25'125	469'333	515'877	10'000	3'180'000
Age	25'125	46	10	28	73
(B) Regional Characteristics					
Apartment Price Growth p.a.	25'125	4.79	2.53	-7.33	13.52
Single-Family Home Price Growth	25'125	4.07	4.07	-3.99	15.27
Number of Online Providers (NOP)	25'125	10.92	2.52	4	14
Herfindahl-Hirschmann Index (HHI)	25'125	0.19	0.05	0.12	0.49
Multi-Market Contact (MMC)	25'125	0.07	0.03	0.05	0.40
(C) Bank Characteristics					
Bank Total Assets (TA)	25'125	16'932	12'841	434	37'804
Mortgages/TA	25'125	69.82	10.43	39.79	90.62
Deposits/TA	25'125	47.80	17.90	16.72	65.63
Capital Ratio	25'125	7.25	1.03	4.72	11.33
Bank Web Experience in Months	25'125	34.39	14.35	0.00	69.00
(D) Response Characteristics					
Distance Applicant Bank HQ (100km)	25'125	1.10	0.87	0.00	4.22
Driving Time Applicant Bank HQ (hours)	25'125	1.30	0.91	0.00	4.42
House price growth correlation	25'125	0.77	0.19	0.15	1.00
Relative Over-Heating (ROH)	25'125	1.16	0.17	0.75	2.08
Responses per Application	25'125	4.24	1.45	1.00	10.00
Response Time in Hours	25'125	97.41	151.72	-2.73	789.10
I (Response in <= 48 hours)	25'125	0.53	0.50	0	1
I (Offer = 1)	25'125	0.82	0.38	0	1
Weighted Offered FP	20'583	7.36	2.93	0.25	10.00
Weighted Rate Offered	20'583	2.16	0.56	0.93	3.25
Weighted Spread Offered	20'583	0.90	0.21	0.49	1.52

Panel (A) shows the characteristics of applications for all responses sent in 2010-2013, so the weight of each application corresponds to the number of responses received, as in the regressions. (B) shows bank-relevant characteristics of the region where the collateral is based. The NOP, HHI and MMC measures of competition vary across the 26 cantons. (C) shows key bank characteristics, as well as the number of months for which the bank has been bidding online, and the fraction of responses sent out in <= 48 hrs. (D) shows key response characteristics. The distance between applicant and bank headquarters is measured once in 100kms and once in hours. House price correlation measures the correlation between year-on-year growth rates in the applicant's and the bank's canton. Relativer over-heating scales the percentage to which house prices in the applicant's canton are deemed overheated by FPRE by the percentage in the bank's home canton. Weighted Spread is the amount-weighted average across the 1-3 tranches offered, where spread is the rate offered less the swap rate for the corresponding maturity prevailing on that day.

Table 2: Competition

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
No. of Online Lenders	0.01***	-0.01***	0.01***	-0.01***	0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HHI in Mortgage Market	0.20***	-0.43***	0.11	-0.36***	0.13*	-0.46***
	(0.07)	(0.04)	(0.07)	(0.04)	(0.08)	(0.04)
Multi-Market Competition	0.17	-0.54***	0.13	-0.64***	0.39***	-0.41***
	(0.14)	(0.09)	(0.14)	(0.09)	(0.15)	(0.09)
Apt. Price Growth	-0.00**	-0.00**	-0.00*	-0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SFH Price Growth	0.00**	0.00**	0.00*	0.00**	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(LTV>=67%)	-0.02**	0.05***	-0.01**	0.05***	-0.01**	0.05***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
I(LTV>=80%)	-0.19***	0.03***	-0.19***	0.03***	-0.19***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(LTI>=4.5)	-0.05***	0.01**	-0.04***	0.00	-0.04***	0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
I(LTI>=5.5)	-0.18***	0.04***	-0.19***	0.03***	-0.19***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Refinancing)	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Ln(Total Assets)			0.01***	-0.05***		
			(0.00)	(0.00)		
Mortgages/TA			0.00***	-0.00***		
			(0.00)	(0.00)		
Deposits/TA			-0.00***	0.00***		
			(0.00)	(0.00)		
Equity/TA			0.01***	0.01***		
			(0.00)	(0.00)		
Constant		1.25***		1.77***		1.26***
		(0.02)		(0.03)		(0.03)
Observations	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.232		0.281		0.311
Estimation	Logit	OLS	Logit	OLS	Logit	OLS
Bank FE	No	No	No	No	Yes	Yes

Columns with unequal numbers show marginal effects from Logit regressions. The number of competitors also bidding for applications in the canton ranges from 4 to 14. Herfindahl-Hirschmann Index (HHI) and Multi-Market Contact (MMC) measures are based on banks' entire existing mortgage portfolios. Apartment and single-family home (SFH) price growth in the applicant's canton is lagged by one year. LTV is the loan-to-value, LTI the loan-to-income ratio of the applicant. About half of all applications are for refinancing a mortgage rather than for initial purchase. All further applicant characteristics (income, wealth, debt, age, house type) are omitted but do not change results when included in addition. All estimations include year*month fixed effects to control for time trends. Standard errors clustered by household (application) in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 3: Risk Management

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price	(7) Offer	(8) Price
Distance in 100km	0.00	0.01***	0.01*	-0.02***	-0.03***	-0.01***	0.01	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Rel. Over-Heating	-0.16***	0.02**	-0.02	0.14***	0.09***	-0.02	-0.25***	0.29***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.06)	(0.02)
Price Correlation	-0.11***	0.09***	-0.05**	0.02*	-0.08***	0.08***	-0.07**	-0.03***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)
I(LTV>=67%)	-0.02**	0.06***	-0.01**	0.06***	-0.01*	0.06***		
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)		
I(LTV>=80%)	-0.19***	0.03***	-0.19***	0.02***	-0.19***	0.03***		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		
I(LTI>=4.5)	-0.04***	0.00	-0.04***	-0.00	-0.04***	0.00		
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)		
I(LTI>=5.5)	-0.18***	0.04***	-0.19***	0.03***	-0.19***	0.03***		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		
I(Refinancing)	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***		
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)			0.01***	-0.05***			-0.00	-0.04***
			(0.00)	(0.00)			(0.01)	(0.00)
Mortgages/TA			0.00***	-0.00***			0.00	-0.00***
			(0.00)	(0.00)			(0.00)	(0.00)
Deposits/TA			-0.00***	0.00			-0.00*	-0.00***
			(0.00)	(0.00)			(0.00)	(0.00)
Equity/TA			0.01***	0.01***			0.01	0.01***
			(0.00)	(0.00)			(0.01)	(0.00)
Constant		0.94***		1.47***		0.97***		1.18***
		(0.02)		(0.04)		(0.03)		(0.05)
Observations	25'125	20'583	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.221		0.274		0.300		0.110
Estimation	Logit	OLS	Logit	OLS	Logit	OLS	Logit	OLS
HH FE	No	No	No	No	No	No	Yes	Yes
Bank FE	No	No	No	No	Yes	Yes	No	No

Columns with unequal numbers show marginal effects from Logit regressions. Driving Distance in 100km between the applicant's postcode and the bank's headquarter has been computed using HERE maps and the –georoute- command by Weber and Péclat (2016). Price correlation refers to year-on-year house price growth in the applicant's and the bank's home canton. Price over-heating in the applicant's home canton, as estimated by FPRE, is scaled by that in the bank's home canton. LTV is the loan-to-value, LTI the loan-to-income ratio of the applicant. About half of all applications are for refinancing a mortgage rather than for initial purchase. All further applicant characteristics (income, wealth, debt, age, house type) are omitted but do not change results when included in addition. All estimations include year*month fixed effects to control for time trends. Standard errors clustered by household (application) in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 4: Rules vs. Discretion in Online Mortgage Pricing

	(1) Price	(2) Discretion	(3) Price	(4) Discretion	(5) Price	(6) Discretion	(7) Price	(8) Discretion
I(LTV>=67%)	0.04***	0.46***	0.04***	0.42***	0.04***	0.44***	0.04***	0.38***
	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.08)
I(LTV>=80%)	0.02***	0.06	0.02***	0.04	0.02***	0.05	0.02***	0.06
	(0.01)	(0.10)	(0.01)	(0.10)	(0.01)	(0.10)	(0.01)	(0.10)
I(LTI>=4.5)	0.00	0.06	-0.00	0.03	-0.00	0.01	0.00	0.02
	(0.00)	(0.10)	(0.00)	(0.10)	(0.00)	(0.10)	(0.00)	(0.09)
I(LTI>=5.5)	0.03***	0.03	0.03***	-0.06	0.03***	-0.01	0.03***	-0.02
	(0.01)	(0.15)	(0.01)	(0.14)	(0.01)	(0.15)	(0.01)	(0.14)
I(Refinancing)	-0.02***	-0.04	-0.02***	-0.05	-0.02***	-0.07	-0.02***	-0.04
	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.07)
I (SFH)	-0.01***	-0.07	-0.01*	-0.00	-0.01***	-0.06	-0.01	-0.07
	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.07)
I (Nonstandard)	0.01**	0.14	0.02***	0.26***	0.01***	0.19**	0.02***	0.16**
	(0.00)	(0.09)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.08)
Ln(Total Assets)	-0.04***	-0.20***	-0.04***	-0.19***	-0.04***	-0.18***	-0.07***	-0.08**
	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)
Mortgages/TA	-0.00***	-0.03***	-0.00***	-0.02***	-0.00***	-0.03***	-0.00***	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Deposits/TA	0.00	0.02***	-0.00	0.01*	0.00***	0.02***	0.00***	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.02***	0.08***	0.01***	0.01	0.02***	0.06*	0.01***	0.08***
	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)
No. of Web Lenders	-0.01***	-0.06***						
	(0.00)	(0.02)						
HHI	-0.26***	-1.05						
	(0.03)	(0.73)						
MMC	-0.55***	-1.76						
	(0.07)	(1.47)						
Distance in 100km			-0.01***	-0.12***				
			(0.00)	(0.05)				
Rel. Over-Heating			0.09***	2.02***				
			(0.01)	(0.25)				
Price Correlation			0.02*	-0.10				
			(0.01)	(0.20)				
I(Fast Response)					-0.01***	-0.18***		
					(0.00)	(0.06)		
Bank Web Experience							0.01***	-0.02***
							(0.00)	(0.00)
Constant	1.41	-0.39	1.37***	-3.11***	1.45***	-1.14	1.17***	-1.69***
	(0.00)	(0.00)	(0.04)	(0.82)	(0.03)	(0.00)	(0.03)	(0.52)
R2	0.28		0.28		0.27		0.22	
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No

Discretion is the variance unexplained in the pricing regressions. Columns 2, 4, 6 and 8 show that it is not orthogonal to key characteristics but varies with them. Bank's Web Experience is the number of months for which the bank has been offering mortgages through the online platform. All other regressors as in Tables 1 and 2 above. Standard errors in parentheses clustered by household (application). * p<0.1, ** p < 0.05, *** p<0.01.

Table 5: Offer Dispersion within each Household

	(1)	(2)	(3)	(4)
	SD	SD	SD/Mean	SD/Mean
No. of web lenders	-0.28***	-0.28***	-0.17	-0.15
	(0.08)	(0.08)	(0.21)	(0.21)
HHI	-26.15***	-25.65***	-20.47**	-18.17**
	(3.59)	(3.61)	(9.36)	(9.25)
MMC	-2.87	-0.58	-5.13	-1.00
	(7.12)	(7.02)	(17.58)	(17.27)
I(LTV>=67%)	4.19***	4.21***	2.74**	2.77**
	(0.40)	(0.41)	(1.34)	(1.37)
I(LTV>=80%)	0.95	1.36	-0.36	0.39
	(0.83)	(0.83)	(1.20)	(1.11)
I(LTI>=4.5)	0.10	0.01	0.30	0.15
	(0.43)	(0.43)	(1.68)	(1.68)
I(LTI>=5.5)	-0.70	-0.63	-2.11	-2.30
	(0.76)	(0.75)	(1.79)	(1.64)
I(Refinancing)	-0.40	-0.30	-3.07**	-2.42*
	(0.38)	(0.39)	(1.53)	(1.30)
Constant	19.69***	20.94***	18.65***	22.25***
	(1.94)	(1.30)	(4.27)	(4.33)
Observations	5'563	5'563	5'563	5'563
R2	0.07	0.04	0.02	0.00
Year*Month FE	Yes	Yes	Yes	Yes

Here we compute the standard deviation (SD) of spreads (amount-weighted where an offer consists of 2 or 3 rather than only 1 tranche) between offered rates and maturity-consistent interest swap rates applicable on the same day across all 1-10 offers an application receives. SD are measured in basis points rather than percentage points to facilitate interpretation. Then Columns 1 and 3 regress that SD on all regressors fixed within an application, while 2 and 4 do so for the SD rescaled by the mean spread a household is offered. Columns 1 and 2 control additionally for year*month fixed effects to proxy amongst others for the prevailing interest rate environment, while Columns 3 and 4 do not. Standard errors in parentheses are clustered by household. * p<0.1, ** p < 0.05, *** p<0.01.

Table 6: Heckman

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price	(7) Offer	(8) Price
No. of Web Lenders	0.03***	-0.01***						
	(0.01)	(0.00)						
HHI	0.64**	-0.51***						
	(0.30)	(0.05)						
MMC	1.72***	-0.35***						
	(0.55)	(0.10)						
Distance in 100km			-0.13***	-0.05***				
			(0.03)	(0.01)				
Rel. Over-Heating			0.34**	0.52***				
			(0.14)	(0.02)				
Price Correlation			-0.35***	0.03				
			(0.13)	(0.02)				
I(Fast Response)					0.14***	0.02***		
					(0.03)	(0.01)		
Web Experience							0.00	0.01***
							(0.00)	(0.00)
I (2nd Semester)	-0.08***		-0.09***		-0.10***		-0.11***	
	(0.03)		(0.04)		(0.04)		(0.04)	
Constant	0.66***	1.13***	1.46***	0.18***	1.46***	0.79***	1.44***	0.60***
	(0.21)	(0.03)	(0.31)	(0.04)	(0.22)	(0.03)	(0.23)	(0.02)
Observations	25'125	25'125	25'125	25'125	25'125	25'125	25'125	25'125
R2		0.14		0.17		0.13		0.27
HH FE	No	No	Yes	No	Yes	No	Yes	No
HH Controls	Yes	Yes	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	MLE	MLE	Probit	Two-Step	Probit	Two-Step	Probit	Two-Step

Columns with unequal numbers display the Heckman first stages, probit regressions of whether the bank's response is an offer on the same regressors as in Tables 1 and 2 plus an indicator for whether the response was sent in months 7-12 rather than 1-6 of the year. Even columns show estimates of the main equation controlling for the non-selection hazard. For reasons of software capacity, Columns 3-8, which control also for household fixed effects, implement this as a two-step procedure. By contrast, Columns 1 and 2 must use household controls instead of fixed effects to avoid collinearity with the competition measures of interest. Without household fixed effects, estimations can be implemented through Maximum Likelihood Estimation (MLE), which improves estimator efficiency. Standard errors clustered by applying household in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 7: Heckman including Non-Responses

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
No. of Web Lenders	0.07***	-0.01***				
	(0.00)	(0.00)				
HHI	-1.96***	-0.58***				
	(0.12)	(0.07)				
MMC	5.29***	-0.32*				
	(0.27)	(0.18)				
Distance in 100km			-0.30***	-0.08***		
			(0.01)	(0.01)		
Rel. Over-Heating			-0.54***	-0.38***		
			(0.14)	(0.03)		
Price Correlation			0.20**	0.09***		
			(0.08)	(0.02)		
Web Experience					-0.00***	0.01***
					(0.00)	(0.00)
I (2nd Semester)	-0.03**		-0.10***		-0.04***	
	(0.01)		(0.02)		(0.01)	
Constant	-2.63***	1.26***	0.47**	0.71***	-1.95***	-0.59*
	(0.06)	(0.18)	(0.19)	(0.08)	(0.04)	(0.33)
Observations	180'839	180'839	48'567	48'567	180'839	180'839
R2		0.14		0.14		0.27
HH FE	No	No	Yes	No	Yes	No
HH Controls	Yes	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	Probit	Two-Step	Probit	Two-Step	Probit	Two-Step

This table repeats the estimations of the previous table after filling in non-responses and treating them like explicit rejections. Columns with unequal numbers display the Heckman first stages, probit regressions of whether the bank's response is an offer on the same regressors as in Tables 1 and 2 plus an indicator for whether the response was sent in months 7-12 rather than 1-6 of the year. Even columns show estimates of the main equation controlling for the non-selection hazard. The two columns analyzing a "fast response" dummy have been dropped as non-responses cannot be categorized as fast or slow. Furthermore, distance could not be filled in for all possible bank household pairs, so that Columns 3 and 4 have fewer observations than the other columns. Standard errors clustered by applying household in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table A1: Geographical Representativeness of Households

	(1)	(2)	(3)	(4)
Canton	Number of Applications	Percentage of Applications	% of Mortgages Swiss Household Panel	% of Volume All Swiss Banks
Aargau	850	12.28	11.70	8.73
Appenzell AR	4	0.06	1.12	0.62
Appenzell IR	33	0.48	0.56	0.18
Basel Land	287	4.15	3.64	3.86
Basel Stadt	106	1.53	0.28	1.92
Berne	982	14.19	17.65	10.77
Fribourg	220	3.18	5.88	3.23
Geneva	162	2.34	2.24	5.06
Glarus	30	0.43	0.84	0.44
Graubünden	163	2.36	1.96	3.33
Jura	26	0.38	0.56	0.75
Lucerne	256	3.70	5.32	4.64
Neuchatel	73	1.05	5.04	1.53
Nidwalden	20	0.29	0.84	0.54
Obwalden	35	0.51	0.84	0.47
Schaffhausen	71	1.03	0.28	0.94
Schwyz	142	2.05	1.96	2.37
Solothurn	238	3.44	2.80	3.37
St.Gallen	339	4.90	6.16	5.73
Thurgau	233	3.37	3.08	3.48
Ticino	182	2.63	3.64	4.73
Uri	17	0.25	0.00	0.40
Valais	223	3.22	3.92	3.59
Vaud	607	8.77	7.28	8.07
Zug	118	1.71	0.56	2.04
Zurich	1'503	21.72	14.29	19.19
Total	6'920	100.00	100.00	100.00

The distribution in our sample counts each of the 6’920 mortgage applications submitted via Comparis.ch once. We can compare it first with the percentages of households in the nationally representative Swiss Household Panel (SHP), provided by the Federal Office of Statistics, who transition to home ownership in 2008-13 and therefore have outstanding mortgage debt in 2014. Finally, we also compare the distribution with that of outstanding mortgage debt already on banks’ balance sheets as reported to the supervisory authority in 2013. Note that the latter is available only based on all mortgages currently on banks’ balance sheets, rather than on new lending only. Based on either comparison, we conclude that the geographical coverage of our mortgage applications is largely representative and is not, for instance, biased towards more urban areas.

Table A2: Geographical Representativeness of Banks

	Comparis		B&M (2018)	
Canton	**# banks**	**% of banks**	**# banks**	**% of banks**
Aargau	2	7.41	3	6.00
Appenzell AR	0	0.00	0	0.00
Appenzell IR	0	0.00	1	2.00
Basel Land	0	0.00	1	2.00
Basel Stadt	2	7.41	4	8.00
Berne	4	14.81	9	18.00
Fribourg	0	0.00	1	2.00
Geneva	1	3.70	1	2.00
Glarus	1	3.70	1	2.00
Graubünden	0	0.00	1	2.00
Jura	0	0.00	1	2.00
Lucerne	1	3.70	1	2.00
Neuchatel	0	0.00	1	2.00
Nidwalden	0	0.00	1	2.00
Obwalden	1	3.70	1	2.00
Schaffhausen	0	0.00	1	2.00
Schwyz	1	3.70	1	2.00
Solothurn	2	7.41	4	8.00
St. Gallen	4	14.81	3	6.00
Thurgau	0	0.00	1	2.00
Ticino	1	3.70	1	2.00
Uri	1	3.70	1	2.00
Valais	1	3.70	1	2.00
Vaud	1	3.70	4	8.00
Zug	0	0.00	1	2.00
Zurich	4	14.81	5	10.00
Total	27	100.00	50	100.00

This table compares the distribution of banks' headquarters across the 26 cantons of Switzerland with that in Basten and Mariathasan (2018), who select the universe of Swiss retail banks based on the FINMA definition that at least 55% of bank income must be net interest income or loan fees, as opposed to stem from own trading or wealth management advisory services.

Table A3: Non-Geographical Representativeness of Households and Banks

A. Comparison of household characteristics with the Swiss Household Panel (SHP)

	Our sample	SHP	Difference
	(1)	(2)	(3)
Age	46.10	45.51	0.60
	(10.21)	(1.17)	(10.45)
Household Income	167'603	147'649	19'999
	(89'061)	(318'066)	(172'429)
Number of observations	25'125	357	25'494

B. Comparison of mortgage risk characteristics with SNB (2014)

	Our sample	SNB	Difference
	(1)	(2)	(3)
Loan-to-Value (LTV) ratio > 80% (0/1)	0.07	0.16	-0.09
	(0.26)	(--)	(--)
Payment-to-Income (PTI) ratio>33% (0/1)	0.39	0.40	-0.01
	(0.13)	(--)	(--)
Number of observations	25'125	(--)	(--)

C. Comparison of bank characteristics with Basten and Mariathasan (2018)

	Our sample	B&M (2018)	Difference
	(1)	(2)	(3)
Total Assets	9'866	12'185	-2'319
	(11'910)	(22'215)	(25'206)
CET1 in % of Total Assets	7.19	7.75	-0.56
	(1.53)	(1.66)	(2.26)
Deposits in % of Total Assets	67.53	47.71	19.83
	(5.47)	(11.00)	(12.28)
Number of observations	27	50	77

Panel A compares households in our sample with those in the Swiss Household Panel (SHP) who recently bought a house or apartment. Panel B compares the 2 key risk characteristics of each mortgage with those reported in the SNB Financial Stability Report 2014, and Panel C compares banks in our sample with the full sample of those 50 Swiss banks focused on deposit-taking and lending. We always compare all characteristics available both in our sample and in the respective benchmark. Column (1) always shows the mean value in our sample and in brackets the standard error. Column (2) shows the respective values for the benchmark sample, except for Panel B where none are given. Column (3) computes the difference and the pooled standard error to evaluate its statistical significance.

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